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# On the Application of a Consumer Preference-Based Method for Designing Products to Wine Fermentation Monitoring Devices

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*This article applies a recently proposed procedure for product design (Bagajewicz, 2007) to the design of a wine fermentation monitoring device. The procedure is based on connections made between consumer preferences and the characteristics of the product; it includes a price-demand model and maximizes the profit by simultaneously changing product characteristics and product price, something that has not yet been applied to devices. We conclude that, unlike other cases, a product that maximizes consumer satisfaction can be successfully marketed. In conclusion, the study is mostly devoted to showing how the methodology applies to this segment of industry, rather than to proposing the best device.*

**Keywords** Consumer preferences; Price-demand model; Product design; Wine fermentation monitoring device

## Introduction

We apply a recently proposed methodology (Bagajewicz, 2007) for product design to the determination of the optimal device that assists fermentation. The original methodology was applied to a consumer product (insect repellent) and has later been applied to a carpet deodorizer (Street et al., 2008), a medical testing device (Heflin et al., 2009), and wine making (Whitnack et al., 2008, 2009). The major features of the methodology rely on the use of microeconomics models to make connections between consumer preferences, product price and structure, and composition and/or functionalities. A compromise between quality of the product (as perceived by the customer) and profit is found. This contradicts directly the premise used by alternative product design procedures, like the one proposed by Cussler and Moggridge (2001) or Seider et al. (2004), who advocate the identification of consumer needs first and use those as targets in the product design procedure. It is important to also point out how this methodology fits into frameworks currently in use by several companies for product development. In particular, one should mention the Stage-Gate$^{TM}$ Product-Development Process (SGPDP) to manage the product design process, once

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the underlying technology has been developed. (Cooper, 2005). In turn, for the technology development phase, Stage-Gate™ Technology-Development Process (SGTDP) has been recently proposed (Cooper, 2001, 2002), which deals with all the innovation phases.

Although the methodology proposed by Bagajewicz (2007) can be used to scope the technology development part, it requires considerations and modeling that have yet to be completed. In fact, the method is mainly applicable to the product development phase. This phase has various stages (concept, feasibility, development, manufacturing, and product marketing). The first two help shape the product based on consumer needs, consumer surveys, and tests. At this stage, the method also suggests building a business case for each product option. Bagajewicz (2007) claims that consumer preferences and behavior against price, as well as manufacturing costs, all treated simultaneously, can help make the best product design choice better at these stages, thus preventing decisions that can later face manufacturing roadblocks (especially cost) or marketing problems (lack of profitability, for example).

Thus, instead of making the process sequential, Bagajewicz (2007) argues that by incorporating elements of all steps, and especially consumer behavior, one can sort out the different product choices better. One example of the usefulness of this methodology is when novel ideas that are technically feasible can be dismissed early on when microeconomics and consumer preferences are considered. For example, a recent study suggested a scenario in which innovation was discouraged because of market preferences and consumer behavior towards prices (Street et al., 2008).

Because of its novelty, one of the questions raised by reviewers and informally in different conference circles regarding a methodology that uses consumer preferences and pricing models, like the one proposed by Bagajewicz (2007), has been that it does not apply well to certain type of products, such as mechanical and electronic devices as well as medical products. Thus, this article focuses on applying the methodology to electronic noses in wine fermentation environments and showing that it can perfectly adapt to these cases, even though the details can be improved and the consumer preference models can be expanded to add more attributes.

Researchers and manufacturers alike have long envisioned creating devices that can "smell" odors in many different applications in environmental modeling, medicine, food industry, etc., detection (Keller et al., 1995; MedGadget, 2005). Thanks to recent advances in organic chemistry, sensor technology, electronics, and artificial intelligence, the measurement and characterization of aromas by electronic noses (or e-noses) has become a commercial reality. "While electronic noses were initially developed as laboratory instruments, science is now moving the technology out of the laboratory and into the workplace, enabling measurements based on smell to be made at the source," says Steven Sunshine, president and CEO of CyranoSciences (Pasadena, Calif., now acquired by Smiths Detection), one of several companies that have commercialized the technology (Ouellette, 1999). Specific materials are being investigated for the construction of theses sensors, which focus on detecting organic vapors in air (Freund and Lewis, 1995).

Electronic noses were used in conjunction with techniques like partial least squares (PLS) for the monitoring of yogurt fermentations (Nayratil et al., 2004). Wine fermentation is also one of the areas where e-noses can actually be of help, especially in detecting different stages of fermentation, as will be discussed in detail in this article. The use of electronic noses in wine fermentation has actually been attempted by Pinheiro et al. (2002), who added organophillic pervaporation enrichment step in conjunction with principal component analysis (PCA) to detect all aroma compounds.

This article is organized as follows. First, background on electronic noses and wine fermentation is given. Then, the proposed device is described and discussed. The consumer preference model is presented followed by the determination of the most preferred product from the consumer point of view. An analysis of profitability follows, indicating that an alternative design is not advisable. We finish with risk analysis. We therefore prove that our methodology can be used to validate/rule out a proposed design, and in the case of validating it, its main characteristics can be outlined. Thus, the article is devoted to illustrating the methodology.



## Electronic Noses

Electronic noses are artificial smelling devices that identify the specific components of an odor and analyze its chemical makeup to identify it. They can learn to recognize almost any compound or combination of compounds. They can even be trained to distinguish between products, like for example, Pepsi versus Coke. Like a human nose, the electronic nose is very versatile, but it is much more sensitive: "E-Nose can detect an electronic change of 1 part per million" (Miller, 2006).

Research in artificial nose technology began as a NASA projected aimed at detecting ammonia leaks onboard the space station (Miller, 2006). Because the human olfactory system is not capable of detecting numerous toxic chemicals until their concentrations are dangerously high, an alternative detection method was needed. Although initially begun as a detection system for toxic chemical leaks, artificial nose technology has spread to many other industries. Current artificial nose applications include those in environmental monitoring, explosives detection, medical diagnostics, and the food industry (Keller et al., 1995).

The two main components of an electronic nose are the sensing system, similar to receptors in human nasal passages, and the automated pattern recognition system, mimicking neurons in the human brain. An odor is induced by molecules, each of which has a specific size and shape that has a correspondingly sized and shaped receptor in the human nose. When a specific receptor attaches to a molecule, it sends a signal to the brain and the brain identifies the smell associated with that particular molecule. Electronic noses based on the biological model work in a similar manner, albeit substituting sensors for the receptors, and transmitting the signal to a program for processing, rather than to a "brain."

The sensing system can be an array of several different sensing elements (e.g., chemical sensors), where each element measures a different property of the sensed chemical, it can be a single sensing device (e.g., spectrometer) that produces an array of measurements for each chemical, or it can be a combination. Generally, electronic noses use a collection of different sensing elements. These sensors are especially designed to conduct electricity. When a substance is absorbed in these sensors, the sensors change how much electricity they conduct. Because each sensor is made of a different substance, each one reacts to each substance, or analyte, in a slightly different way. Finally, while the changes in conductivity in a single sensor would not be enough to identify an analyte, the varied changes in various sensors produce a distinctive, identifiable pattern.

Each multicomponent chemical vapor presented to the sensor array produces a signature or pattern characteristic of the vapor, a digital "fingerprint" of the specific odor. By presenting many different chemicals to the sensor array, a database of "fingerprints," or more appropriately "smell-prints," are built up. This database of labeled signatures is used to train the pattern recognition system. The goal of this training process is to configure the recognition system to produce unique classifications of each chemical so that an automated identification can be implemented. Artificial neural networks (ANNs), which have been used to analyze complex data and to recognize patterns, are showing promising results in chemical vapor recognition.

This combination of a sensing system with a pattern-recognition system enables e-noses to process new odors based on patterns of aromas created by earlier experiences, which is similar to the way the human olfactory system works.



## Wine Fermentation

Fermentation in wine is the process whereby yeast converts sugar into carbon dioxide and ethyl alcohol (ethanol). There are three stages of fermentation (Eismann, 1999):

- Primary or aerobic (with air) fermentation
- Secondary or anaerobic (without air) fermentation
- Malolactic fermentation (possible third stage)

During the primary fermentation of wine, glucose and fructose are converted to alcohol (ethanol) by the action of yeast. Carbon dioxide is also produced and leaves the solution in gaseous form, while the alcohol is retained in the mix. The by-products of primary fermentation are aromas, flavors, and heat. This stage generally lasts for about a week and is a critical stage for yeast reproduction. On average, 70% of fermentation activity occurs during these first few days. There is vigorous action as a result of the rapid fermentation that often results in considerable foaming on the surface. Primary fermentation is usually conducted in an open container, hence the "aerobic" part of the term, covered with a clean tea towel known as the "primary fermentation vessel."

Secondary fermentation is the process where the remaining 30% of fermentation activity occurs. It is a much more gentle process that usually lasts anywhere from two to three weeks to a number of months, depending on the amount of nutrients and sugars still available. Secondary fermentation takes place in a fermentation jar fitted with an airlock, hence the term anaerobic. The occasional bubbling of the airlock is often a signal that carbon dioxide is still being produced.

Malolactic fermentation is a possible third stage that can occur sometimes after the original fermentation process has ended, even a year after bottling. A continuation of the fermentation in the bottle is to be avoided as it can result in a buildup of carbon dioxide, which can cause bottles to burst. Furthermore, it often results in a semi-carbonated wine that does not taste good. Therefore, this stage is often induced after secondary fermentation but before bottling, by inoculating the wine with bacteria. The bacteria, lactobacilli, will convert malic acid into lactic acid. A small amount of carbon dioxide is released, which in extreme circumstances can produce a semi-sparkling wine, but the main result is that lactic acid has about half the acidity of malic acid and this produces a somewhat less acidic wine with a much cleaner, fresher flavor.

## Monitoring Wine Fermentation

### *Malolactic Fermentation Control*

It is imperative for wineries who employ this flavor-controlling process to be able to initiate malolactic fermentation early enough to avoid its continuation after bottling and consequently avoid the production an inferior product that would ultimately result in a loss of profit.

### *Champagne and Sparkling Wine Production*

Champagnes and sparkling wines are produced by adding rock sugar and supplementary yeast to partially fermented wine after the primary stage of fermentation has occurred, but prior to the onset of the secondary stage. This combination of ingredients results in the characteristic carbonation found in champagnes and sparkling wines. In order to minimize the production time and thus maximize profit, it is imperative that champagne and sparkling wine producers know precisely when their batches have completed primary fermentation so that they can add the appropriate ingredients to achieve their final product sooner and then proceed with the production of a new batch with as little down time as possible.

### *Champagne and Sparkling Wine Bottling*

In order for champagnes and sparkling wines to be bottled, the fermentation process must be stopped or severely reduced to avoid carbonation buildup in-bottle, which often results in an unsafe product. Bottles have been known to explode due to carbonation buildups and many times a chain reaction will be initiated where one bottle after another explodes, causing the entire stock to be destroyed. Because the wine and sparkling wine industries are centered around a single-year production, from the grape harvest to the final product that must mature for a certain amount of time, often years, before being ready for distribution, a loss can be economically devastating. If a year's stock is ruined, the winery must wait a full year before beginning the next production process, resulting in an entire year's loss of revenue in the future. Knowing precisely when the fermentation process has ceased is therefore extremely beneficial to wine and sparkling wine producers. This knowledge would insure that unsafe levels of carbonation did not build up in-bottle and would ultimately give more economic security to a relatively risky industry.

### *Additives to Manipulate Wine Characteristics*

Two major characteristics of wine are sweetness and alcohol content. Control of these characteristics can be achieved by adding additional nutrients and/or adding yeast-retarding products to the mix. Sweetness can be increased by adding additional sugars to the partially fermented stock, whereas adding yeast-retarding agents impairs and ultimately destroys yeast cells, causing fermentation to cease, resulting in a product with specific alcohol content. In order to achieve a specific, desired product, it is crucial to be able to use these additives at the appropriate time. Waiting too long or adding them too soon will result in either a bitter product with too high alcohol content or an overly sweet product with a low alcohol content, neither of which are desirable by the majority of wine consumers. Being able to precisely know when to use additives is beneficial because it allows for the production of a specifically defined product, one that was designed based on key characteristics desired by the majority of the market.

## The Device Design

The design objective of the device (we call it Wi-Nose) is to provide the wine industry with a lightweight, compact, and accurate sensing device. Other design factors that were considered included ease of installation, level of maintenance, and lifetime of the device. The Wi-Nose consists of a rigid, plastic hemisphere that contains a sensor array, a microprocessor with RAM, a wireless transmitter, and a pneumatic pump (Figures 1 and 2). The sample of the test gas enters the device through a small intake. The pneumatic pump provides the pressure differential necessary for the sample to enter the device. The sample is then directed towards the sensor array, where it accumulates in the device headspace. Once in the headspace, the sample gas interacts with the sensor array and is then expelled through the sample exhaust. The sensor array contains three sensors, two metal oxide sensors for the detection of ethanol and one electrolyte sensor for the detection of carbon dioxide.

Upon interaction with the sample gas, the sensors send their respective output signals to the microprocessor where the information is stored in the device's RAM and then transformed and sent to the wireless transmitter. The wireless transmitter sends the data to the hub computer where the information is classified with the aid of an artificial neural network. The proposed system allows for the addition of multiple devices for the monitoring of multiple products. By having all devices transmit their signals to the same computer, the consumer will be responsible for purchasing only a single artificial neural network, a program that accounts for a large percentage of the device's cost.

The Wi-Nose is designed to be easy to install. Four screws and hex nuts are included with the device, as well as multiple rubber O-rings to prevent moisture from



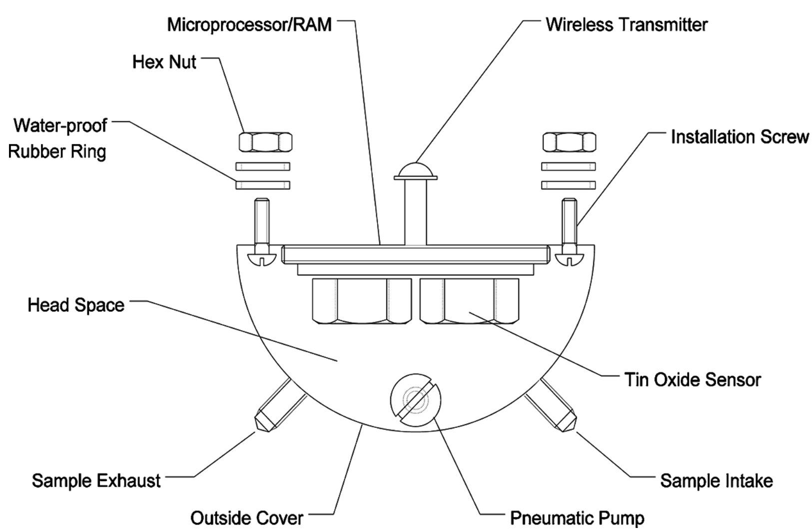


**Figure 1.** Cross-sectional view of the Wi-Nose.

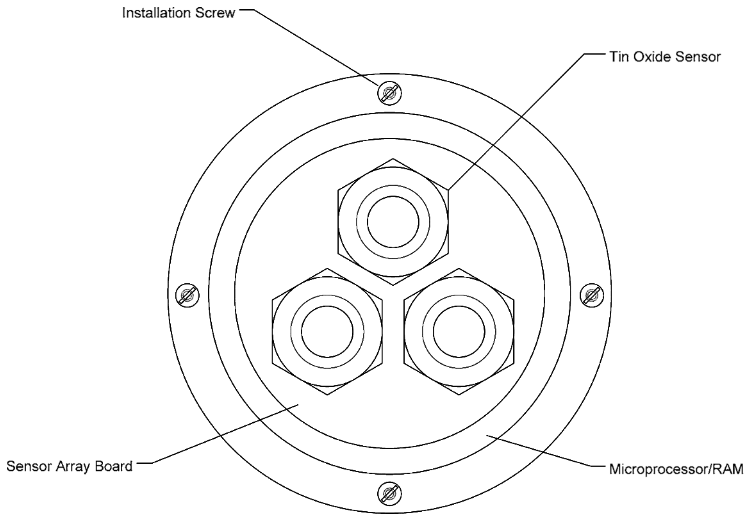


**Figure 2.** Top view of Wi-Nose device.



contacting the metal components. Because most of these units are to be installed in metal fermentation vats or tanks, it is important to reduce the risk of rusting. Moisture control issues are bound to be encountered, and the Wi-Nose is designed specifically with these potential problems in mind. Moisture buildup is directed away from the metal interface and sensitive device components due to the apparatus's unique shape. The hemisphere design allows for condensation to run down outside of the plastic cover and drip off the device without damaging the water-sensitive components housed inside.

This design also promotes device longevity. The Wi-Nose has a minimum lifetime of five years. The device should be tested on a semi-regular basis throughout the first five years to guarantee that it is providing reliable results, however, the sensors should be replaced and the device should be serviced every six to seven years. Usually, the only parts that should have to be replaced at this time are the sensors; however, they are of relatively low cost and replacing them on this timetable should not amount to much cost to the consumer.

### *Sensor Choices*

Three different sensors are used in the Wi-Nose design. The first is Figaro's TGS 822 for the detection of ethanol. The TGS 822 is a tin oxide sensor that features the following characteristics (Figaro, 2009):

- High sensitivity to organic solvent vapors such as ethanol
- Unresponsive to carbon dioxide
- High stability and reliability over a long period (lifetime $\geq$ five years, up to 200°C)
- Long life and low cost

It uses a simple electrical current to produce a resistance output in response to a detectable gas's concentration (ppm) (Figure 3). Because the TGS 822 is unresponsive to carbon dioxide, this allowed for its easy integration into the Wi-Nose.

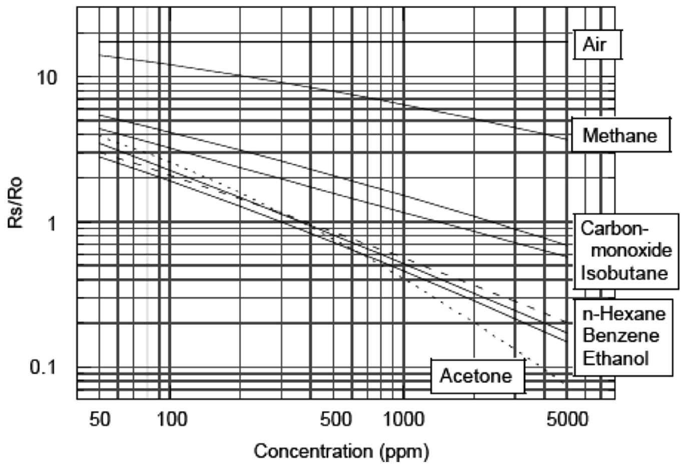


**Figure 3.** Resistance vs. concentration for the sensor Figaro TGS 822.

This characteristic eliminates carbon dioxide's effect as an interference gas and ultimately removes carbon dioxide hindrance from the design parameters.

The Wi-Nose also features another metal oxide sensor for the detection of ethanol, the Figaro TGS 2620. This sensor is based on an alumina substrate and features the following characteristics (Figaro, 2010a):

- Low power consumption
- High sensitivity to alcohol and organic solvent vapors (Figure 4)
- Unresponsive to carbon dioxide
- Long life and low cost

Finally, the TGS 4160 has the following features (Figaro, 2010b):

- High selectivity for carbon dioxide (Figure 5)
- Unresponsive to ethanol

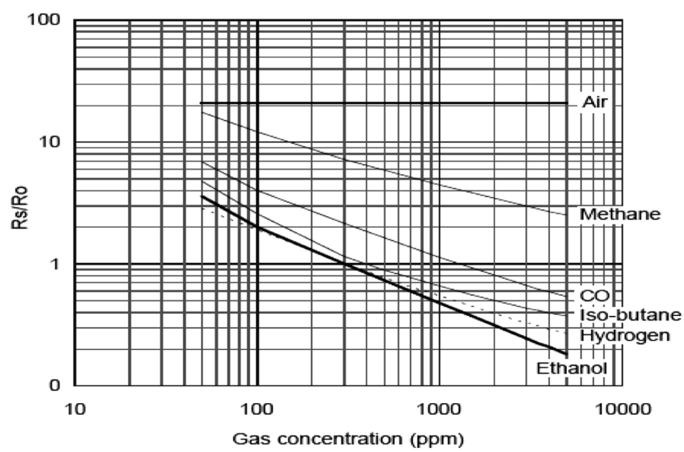


**Figure 4.** Output signal vs. concentration for the sensor Figaro TGS 2620.

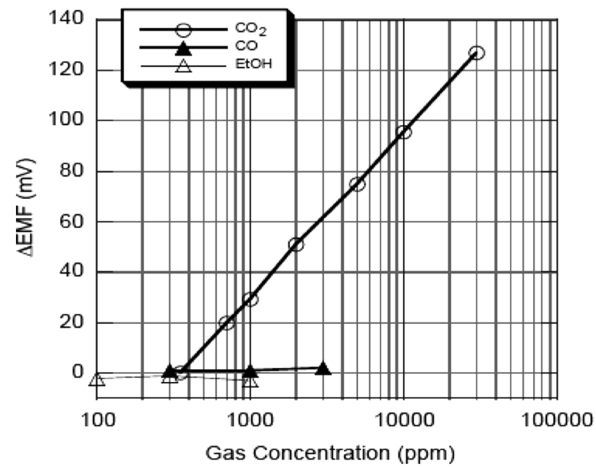


**Figure 5.** Output signal vs. concentration for the sensor Figaro TGS 4160.

- Compact size
- Long life

The TGS 4160 differs from both the TGS 822 and the TGS 2620 because it is an electrolyte sensor. It utilizes electromotive force to create a signal output that corresponds to a detectible gas concentration. Unlike the previous two sensors, the TGS 4160 is unresponsive to ethanol, making it an excellent choice for the same reason that the TGS 822 and the TGS 2620 were good choices based on their insensitivity to carbon dioxide.

The next step was to train a neural network using all these data. The use of a neural network can be justified because although it seems that this analysis simply consists of the determination of the stage of fermentation as a function of two concentrations, the situation is more complex. Due to the products of fermentation, ethanol and carbon dioxide, being produced in unequal amounts in the gaseous phase (carbon dioxide is produced in much greater quantities than ethanol in the gaseous phase), the measurements of these gaseous elements will have different associated errors at different times throughout the fermentation process. At the beginning of the fermentation process, the amount of gaseous ethanol concentration will be very small, while the carbon dioxide concentration will be much more substantial. Therefore, any error associated with the gaseous ethanol concentration will be a large percentage of the actual measurement. This implies that the carbon dioxide concentration should have more weight in determining the overall stage classification than the gaseous ethanol concentration at the beginning of the fermentation process. As the process continues, both the gaseous ethanol and carbon dioxide concentrations will continue to increase until the carbon dioxide concentration reaches a high enough level to saturate the sensor, at which time the carbon dioxide concentration data will become unreliable and the gaseous ethanol concentration should have more weight in the stage classification. The neural network not only allows for different measurements to carry different weights in the overall classification, it also allows for the addition of more sensors, including sensors that can detect more than one gas.

The program used to develop the neural network model was NeuroSolutions 5 from NeuroDimension, Inc. (Gainesville, Fla.). The goal was to train a neural network to classify the stages of fermentation as first, second, or third. Data were collected from 2458 samples: 1741 for the first stage, 692 for the second stage, and 25 for the third stage. The samples were randomized using a built-in preprocessing data function. Three columns were defined as input variables: TGS 822 Rs/Ro, TGS 2620 Rs/Ro, and TGS 4160 EMF. Three columns were defined as the desired output: Stage 1, Stage 2, and Stage 3. A certain percentage of the rows were tagged as training samples. A certain percentage of the rows were tagged as cross-validation. Cross-validation is a very useful tool to prevent what is known as over-training. Finally, a certain percentage of the rows were tagged as testing to define samples to be used for testing the trained network. Several runs using 1000 epochs each were completed, each varying the number of training, cross-validation, and testing percentages. The best training was then determined resulting in an accuracy of 100% for all stages.



## The Market

The number of wineries in the U.S. is approximately 4,385. The proposed market is California, because it accounts for 90% of American wine production (WineBusiness.com, 2007).

## Consumer Preference Model

The first step of the methodology is to assess consumer preferences. We use a linear weighted average of consumer preferences of specific characteristics:

$$H_{ik} = \sum_j w_{ikj} y_{ikj} \tag{1}$$

where $H_k$ is the preference for product $i$ in market $k$, $y_{ik}$ is the score of the product characteristics $j$ for product $i$ in market $k$, and $w_{ik}$ is the corresponding weight. The design characteristic weights and scores are often generated by informal surveys in which the consumer ranks the design characteristics in the order of importance and provides preference information that relates customer satisfaction to product attributes. This illustrates that customer preference is a function of product design.

Design characteristics that were altered in the development of the Wi-Nose were accuracy, device size, and device weight. The weights of the design characteristics are calculated using a point system in which votes for the most important design characteristic received the most points and votes for the least important device characteristic received the least points. This informal customer preference survey resulted in the design characteristic weights shown in Table I.

**Table I.** Design characteristics' weights

| Design characteristic | Weight |
|---|---|
| Accuracy | 0.2 |
| Size (cc) | 0.15 |
| Weight (pounds) | 0.65 |

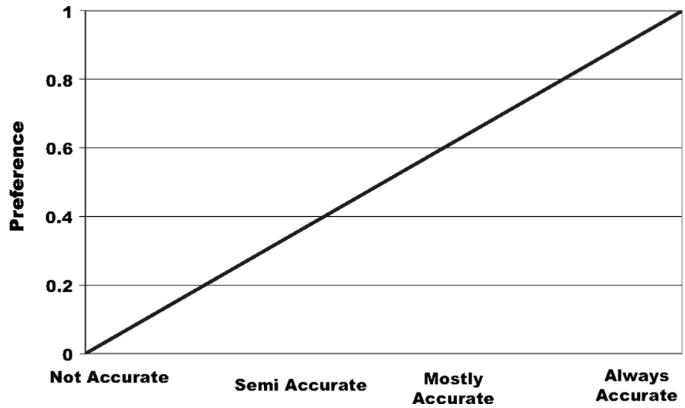


**Figure 6.** Preference vs. accuracy of device.



Customer preference functions for each device characteristic were also generated from the customer preference survey. Each of these preferences is analyzed next.

### *Accuracy*

Figure 6 represents the customer's satisfaction based on the accuracy of the device. This accuracy information is then related to actual device percentage correct classification in Figure 7. Any percentage correct classification rate below 60% would define not accurate, in the range of 60–75% would define semi-accurate, in the range of 76–90% would define mostly accurate, and in the range of 91–100% would define always accurate. Finally, customer satisfaction is related to actual device percentage correct classification in Figure 8.

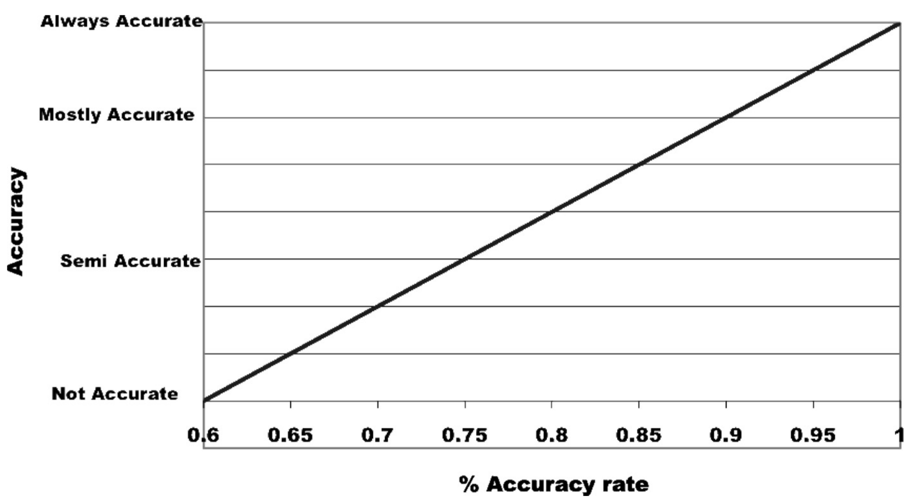


**Figure 7.** Accuracy of device vs. percent accuracy rate.

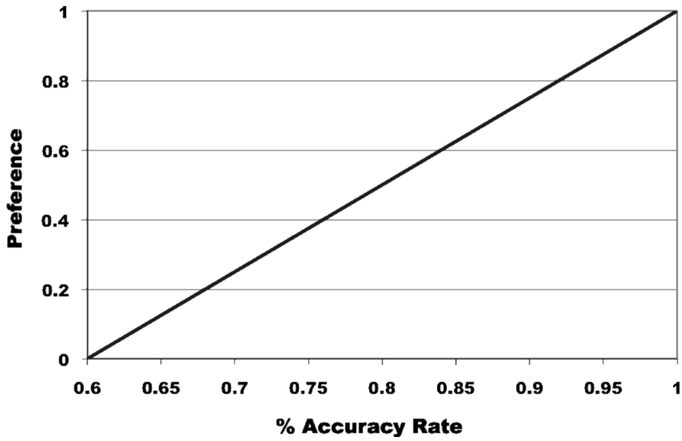


**Figure 8.** Preference vs. percent correct classification.

### *Device Weight and Size*

Customer satisfaction was related to device weight descriptions, and those same device weight descriptions were then related to actual device weight measurements (lbs). These actual device weight measurements were then correlated with customer preference. Similarly, customer preference was related to device size descriptions, and those descriptions were then related to actual device size measurements (cc). In turn, these actual device size measurements were correlated to customer preference. The customer satisfaction plots for both of these device characteristics are presented in Figures 9–14.

We therefore have three characteristics: Accuracy, which can be manipulated by the choice of sensors, weight, and size, which can be manipulated mechanically. Price is sometimes considered in consumer preference models that do not include a pricing model. In our case, our pricing model establishes the response of consumers to price separately from their preferences for the product quality.

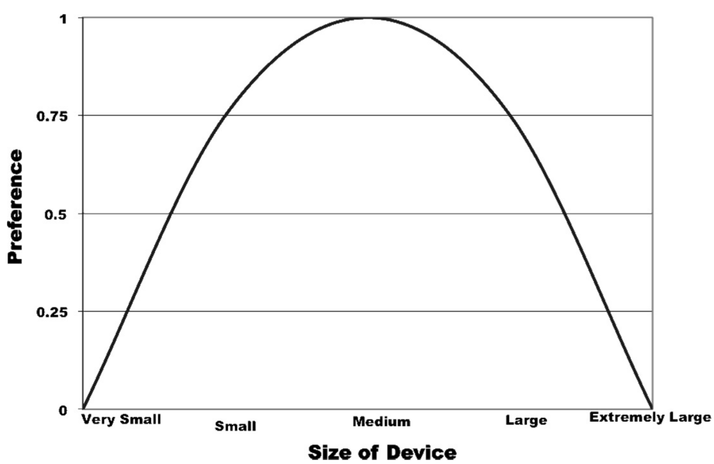


**Figure 9.** Preference vs. size of device.

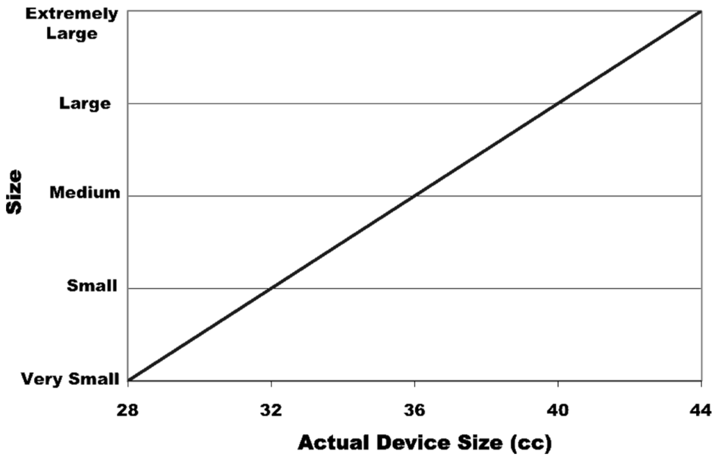


**Figure 10.** Size assessment.



## Pricing Model

We use a constant elasticity model proposed by Bagajewicz (2007):

$$p_1 d_1 = \left(\frac{\alpha}{\beta}\right)^{\rho} p_2 \left[\frac{Y - p_1 d_1}{p_2}\right]^{1-\rho} d_1^{\rho} \tag{2}$$

In this expression, $d_1$ is the demand of the new product, and $p_1$ and $p_2$ are the corresponding prices for the new and the existing product. Finally, $Y$ is the consumer maximum budget for this product. The demand of the existing product is derived from the budget constraint ($d_1 p_1 + d_2 p_2 = Y$). In turn, $\alpha$ is the awareness function (zero when consumers are not aware of the new product and one when they are fully aware), and $\beta$ is the product superiority function, which is the ratio of the consumer

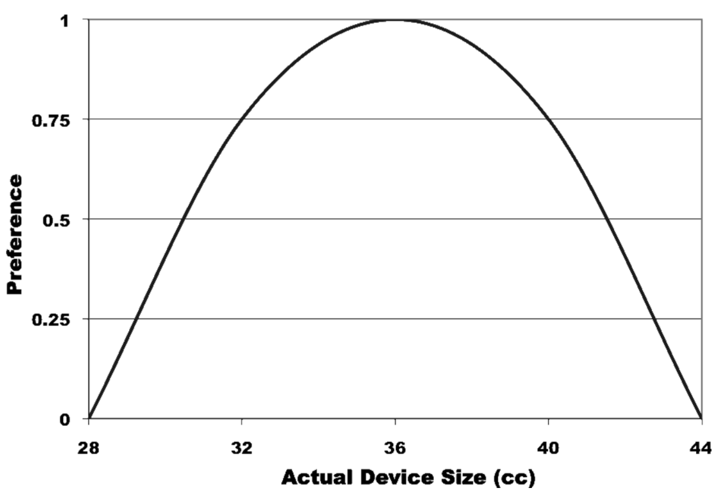


**Figure 11.** Preference vs. device size.

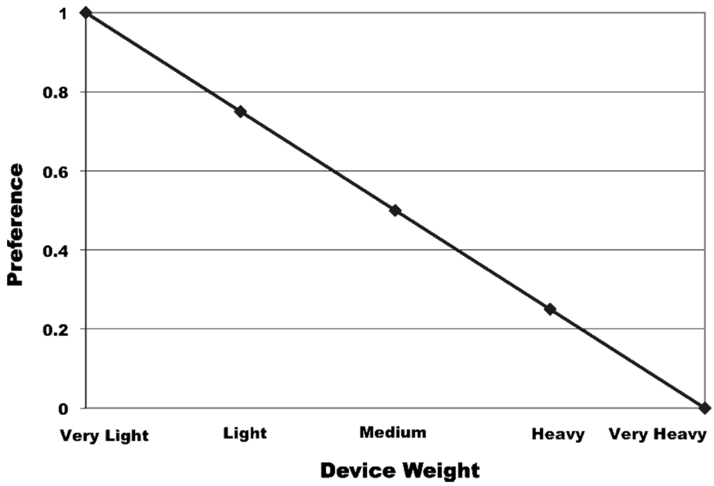


**Figure 12.** Preference vs. device weight.

preferences ($\beta = H_2/H_1$). Finally, $\rho$ is a parameter (related to the elasticity). Bagajewicz (2007) discussed in detail the advantages and shortcomings of the above model in view of other alternatives.

## Maximum Consumer Preference

We now determine the product that maximizes consumer preference. We assessed the preferences of our device and that of the competitor (Table II). For our device, we use the values that give maximum preference. In the next section, we investigate if this is profitable or if a different product needs to be manufactured (we find it is the most profitable). The competitor is Cyranose 320, an e-nose produced by

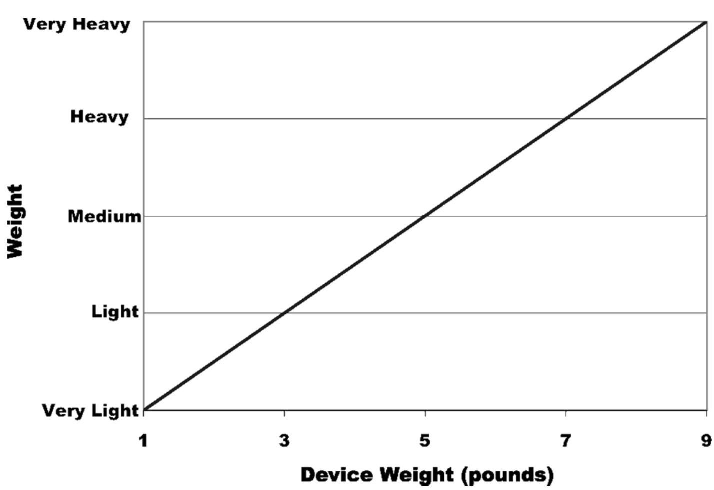


**Figure 13.** Weight assessment.

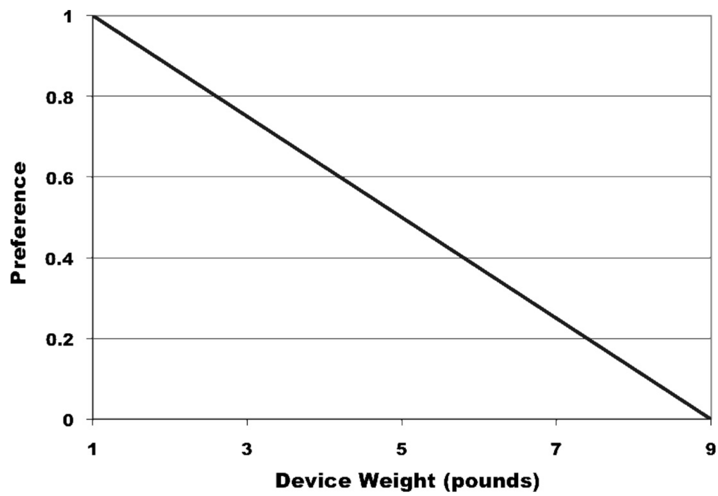


**Figure 14.** Preference vs. device weight.



**Table II.** Preference functions

| Device characteristic | Our device | $y_i$ Our device | Cyranose 320 | $y_i$ Cyranose |
|---|---|---|---|---|
| Accuracy | 100% | 1 | 75% | 0.75 |
| Size (cc) | 36 | 1 | 43.8 | 0.005 |
| Weight (lbs) | 1 | 1 | 2.5 | 0.8125 |
| Consumer preference | $H_1 = 1$ | | $H_2 = 0.6$ | |

CyranoSciences (recently acquired by Smiths Detection, http://www.smithsdetection.com/eng/index.php), which has a weight of 2.5 lbs and whose size is approximately that of a walkie-talkie, that is 43.8 cc. Currently the Cyranose 320 is used in diverse industries including petrochemical, chemical, food, packaging, plastics, pet food, and many more. Thus, the accuracy in regards to wine fermentation stage is hard to determine. An accuracy value of 75% was assumed. This value can be treated as an uncertain parameter to later assess expected profits. The assumption, however, does not change the design of the best product. The price for the Cyranose 320 is $10,000.

## Profit Maximization

We now apply the procedure outlined by Bagajewicz (2007) with the decomposition procedure he suggested. This procedure relies on the following steps:

1. A value of $\beta$ (superiority) is picked and fixed.
2. The product is designed targeting this value of $\beta$ at minimum cost.
3. The demand is determined using Equation (2) for different values of price.
4. Based on this demand and price, the operating costs associated and the capital cost, the net present worth (NPW) is obtained.

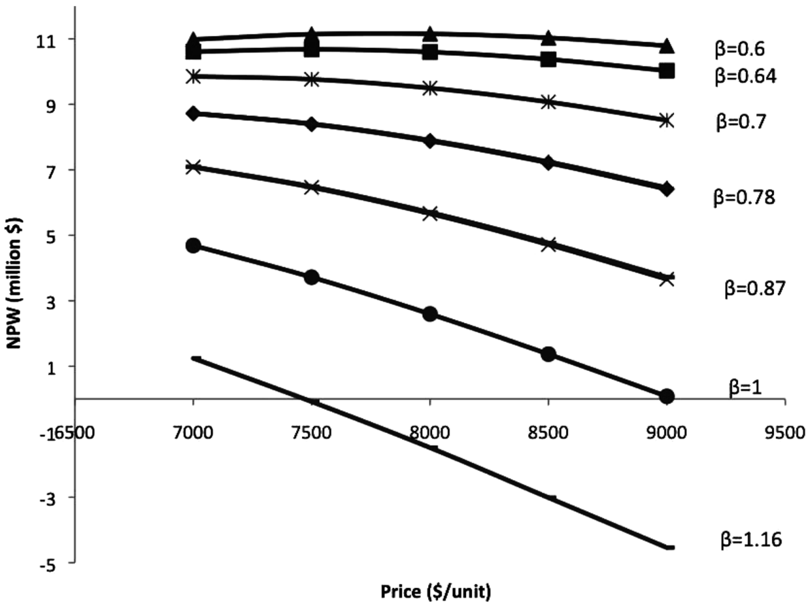


**Figure 15.** NPW 1 vs. product price.

The procedure outlined above allows plotting the NPW as a function of price for different values of beta. We do this in this study for one market and one competitor, but it can be extended to multiple competitors (Street et al., 2008). Results are shown in Figure 15.

The product with $\beta = 0.6$ (the best product) proves to be the most profitable product. It has a total annual cost of raw materials of \$2.07 million, with a total capital investment (TCI) of \$6.514 million for the optimal price of \$8,000 with a demand of 1651 units. The return on investment (ROI) is 49.2% with a payback period of 1.5 years. Advertisement and distribution costs were not computed and the inferiority function $\alpha$ was considered to be 1, instead of a smaller value, so these values are in reality lower, but they do not differ from one product to another. Finally, there is the uncertainty introduced by lack of knowledge of the accuracy of the competitor's product.

Generally, the optimal satisfaction product is not the most profitable because of the costs associated in giving it these best characteristics. With the Wi-Nose, however, the optimal happiness product was also the most profitable. This is because the only characteristics that were varied (size and weight) had very little cost associated with them (cover, \$2/unit; board, \$1.50/unit; wiring, \$2/unit). This is unlike other cases in which the product has numerous properties that are manipulated, and the costs associated with these variables are much more significant.

## Risk Analysis

We notice that even if the $\beta$ value was equal to 1, the NPW is still positive. Depending on the price set for the Wi-Nose, an NPW of up to 5 million is still possible in this instance, which takes care of a good portion of the uncertainty of the quality.

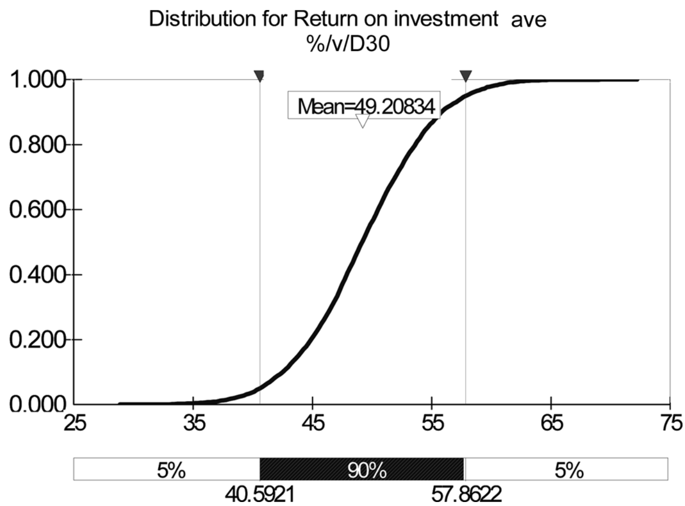


**Figure 16.** Risk analysis graph.

To evaluate the risks associated with the Wi-Nose, a risk analysis was performed using Palisade Decision Tools @Risk 4.5 for Excel. Since the raw materials were what differed with each product design, a 20% variability in raw material costs, using a normal distribution, was used. The desired output for the risk analysis was ROI. Using Monte Carlo sampling type and 10,000 iterations, a histogram and risk curve were produced.

There is a 90% probability that the Wi-Nose will have an ROI between 40.6% and 57.9% (see Figure 16). Thus, under the given setting and conditions, this is a profitable venture.

## Conclusions

An artificial sensing device, the Wi-Nose, can be successfully designed to monitor the fermentation stages in wine. With the aid of neural networks, 100% accuracy is possible to achieve. The product featuring maximum consumer satisfaction, which is better than the competition, can be marketed optimally at a price slightly lower than the competitor price.

Thus, in this article we have shown that the methodology proposed by Bagajewicz (2007) can be applied to the design of electronic devices. The advantages of using this methodology are that the new ideas can be tested against consumer preferences and associated demand at early stages of the design process. In the particular application of this study, one can conclude that through this early study further development is warranted.

## References

Bagajewicz, M. (2007). On the role of microeconomics, multi-scale planning and finances in product design, *AIChE J.*, **53**(12), 3155–3170.

Cooper, R. G. (2001). *Winning at New Products: Accelerating the Process from Idea to Finish*, 3rd ed., Perseus Pub., Cambridge, Mass.

Cooper, R. G. (2002). *Product Leadership: Creating and Launching Superior New Products*, Perseus Pub., Cambridge, Mass.

Cooper, R. G. (2005). *Product Leadership: Pathways to Profitable Innovation*, 2nd ed., Basic Books, New York.

Cussler, E. L., and Moggridge, G. D. (2001). *Chemical Product Design*, Cambridge University Press, New York.

Eismann, L. (1999). *The Home Winemakers Manual*, http://www.geocities.com/lumeisenman/winebook.pdf

Figaro USA. (2009). Product Information: TGS 822 – for the detection of Organic Solvent Vapors, http://www.figarosensor.com/products/822pdf.pdf

Figaro USA. (2010a). Product Information: TGS 2620 – for the detection of Solvent Vapors, http://www.figarosensor.com/products/2620pdf.pdf

Figaro USA. (2010b). Product Information: TGS 4160 – Technical Information, http://www.figarosensor.com/products/4160pdf.pdf

Freund, M. S., and Lewis, N. S. (1995). A chemically diverse conducting polymer-based electronic nose, *Proc. Natl. Acad. Sci. Chem.*, **92**, 2652–2656.

Heflin, L., Walsh, S., and Bagajewicz, M. (2009). Design of medical diagnostics products: A case-study of a saliva diagnosis kit, *Comput. Chem. Eng.*, **33**(5), 1067–1076.

Keller, P. E., Kangas, L. J., Liden, L. H., Hashem, S., and Kouzes, R. T. (1995). Electronic noses and their applications, in IEEE Northcon/Technical Applications Conference (TAC'95), http://cns-web.bu.edu/pub/laliden/WWW/Papers/nose.html (accessed Feb. 1. 2008).

MedGadget. (2005). E-nose to detect lung CA, http://medgadget.com/archives/2005/04/enose_to_detect.html (accessed Feb. 1, 2008).

Miller, K. (2004). Electronic nose, http://science.nasa.gov/headlines/y2004/06oct_enose.htm (accessed Feb. 1. 2008).

Navratil, M., Cimander, C., and Mandenius, C.-F. (2004). On-line multisensor monitoring of yogurt and filmjolk fermentations on production scale, *J. Agric. Food Chem.*, **52**, 415–420.

Ouellette, J. (1999). Electronic noses sniff out new markets, *Ind. Phys.*, **5**(1), http://www.aip.org/tip/INPHFA/vol-5/iss-1/p26.pdf (accessed Feb. 1, 2008).

Pinheiro, C., Rodrigues, C. M., Schafer, T., and Crespo, J. G. (2002). Monitoring the aroma production during wine-must fermentation with an electronic nose, *Biotechnol. Bioeng.*, **77**(6), 632–640.

Seider, W. D., Seader, J. D., and Lewin, D. R. (2004). *Product and Process Design Principles*, John Wiley, New York.

Street, C., Woody, J., Ardila, J., and Bagajewicz, M. (2008). Product design: A case study of slow release carpet deodorizers/disinfectants, *Ind. Eng. Chem. Res.*, **47**(4), 1192–1200.

Whitnack, C., Heller, A., and Bagajewicz, M. J. (2008). A microeconomics-based approach to product design under uncertainty, in: *18th European Symposium on Computer Aided Process Engineering, ESCAPE 18*, Elsevier, Oxford.

Whitnack, C., Heller, A., Frow, M. T., Kerr, S., and Bagajewicz, M. J. (2009). Financial risk management in the design of products under uncertainty, *Comput. Chem. Eng.*, **33**(5), 1056–1066.

WineBussiness.com. (2007). Number of wineries tops 5,900, http://www.winebusiness.com/news/dailynewsarticle.cfm?dataId=45971.